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Parking Occupancy and External Walking Costs in Residential Parking Areas

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Abstract

We estimate the effect of parking occupancy on distances walked between parking and residential locations in Amsterdam. Using data from scanner cars, we show that walking distances only increase when the occupancy rate exceeds 85 per cent. However, the marginal effect of occupancy on walking beyond 85 per cent is limited: every parker imposes 8 m on each subsequent parker. Our analysis suggests it is optimal to have almost all parking spaces occupied late in the evening when few residents aim to park. Our result has important consequences for policy makers who use residential parking permits to prevent cruising for parking.

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1.0 Introduction

In many cities around the world, policy makers aim to influence residential parking demand, and therefore cruising for parking, by using non-price policy measures. In some countries, local governments regulate the occupancy rate by providing residential parking permits which allow for unlimited parking by residents, but at the same time restrict the number of residential parking permits per household. This raises the more fundamental question: what is the optimal occupancy rate in residential areas? According to economic theory, policies for residential parking must take into account the external costs and benefits of parking (Zakharenko, 2016). Intuitively, when the occupancy rate is high, parkers impose walking and search costs on subsequent parkers, and therefore create an externality. Arguably, a high occupancy rate also contributes to traffic congestion, accident risks, and pollution (Shoup, 2006). When the occupancy rate is low, parking spots are not used efficiently. In the current paper we estimate the external costs that a residential parker imposes on other residents who arrive during the period that the residential parker remains parked (Zakharenko, 2016), and compare these costs to the benefit of parking by residents.

Our paper relates to a literature which aims to understand the effect of policy on occupancy rates and therefore on the external cost of parking. For example, Shoup (2006) suggests using a straightforward approach, where parking prices are set so that the average occupancy rate does not exceed 85 per cent, which essentially eliminates all cruising for parking. This rule, which implicitly assumes that the external cost (the sum of in-vehicle search costs and walking costs) starts to exist above an occupancy rate of 85 per cent, is known as the *Shoup rule-of-thumb*. More recent work shows that the optimal occupancy rate is not a constant, but also depends on the arrival rate of new parkers relative to parking capacity (Arnott, 2014; Zakharenko, 2016). We shall take this into account.

There are two reasons why the *Shoup rule-of-thumb* may be too stringent in a residential context. First, while there are technical reasons for a convex relationship between occupancy and the average number of spaces inspected before finding a vacant parking space, we may expect that the effect of occupancy on *searching* is lower in a residential context.[1] The main reason is that residents aim to park in front of their houses; hence, the spatial differentiation of parking demand in residential areas is far greater than in other situations, including CBD parking and shopping centre parking, where parkers aim to park at similar destinations. Therefore, residential parkers arriving in a street with a high occupancy rate will have a high chance of finding remaining vacant spots near their own residence. Second, in residential areas there is often a specific relation between arrivals and parking occupancy: the latter tends to increase as the evening progresses, while the arrival rate tends to decrease, which reduces the external costs of parking. Martens *et al.* (2010) show that such patterns push the optimal occupancy rate upward (up to 93 per cent). In the current paper, we empirically examine to what extent

[1] Let us suppose that the probability of finding an empty space equals 1 minus the (average) occupancy rate for each inspected parking space. The expected number of inspected spaces before finding a vacant one then equals $1/(1 - occupancy)$ (Arnott and Williams, 2017). With occupancy rates of 0.6, 0.7, 0.8, and 0.9, the expected number of inspected spaces are 2.5, 3.3, 5, and 10, respectively, so this relationship is highly convex.

the *Shoup rule-of-thumb* holds in a residential context by focusing on the external walking distance imposed by high residential parking occupancy rates.

Our study on residential parking differs from the majority of parking studies which deal with parking in business and shopping districts. The literature on residential parking is scarce and primarily concerned with the effects of minimum parking requirements on road congestion and car ownership (Weinberger *et al*., 2009; Guo, 2013).[2] One exception that is relevant to our study is a study by Van Ommeren *et al*. (2011), which uses house price data from Amsterdam to demonstrate that the sum of search and walking costs for residents with residential parking permits who park on-street are non-negligible and about €1.15 per day. This suggests that high parking occupancy is a relevant issue in the context of residential parking in Amsterdam.

Two recent studies found evidence for the *Shoup rule-of-thumb*. Millard-Ball *et al*. (2014) used parking inflow and outflow data from a parking experiment in a non-residential context in San Francisco, and found that beyond an occupancy rate of 85 per cent, the probability of finding a vacant parking spot quickly becomes zero. Using a similar methodology, but controlling extensively for endogeneity, Inci *et al*. (2017) found that the inflow of parking cars in a shopping street in Istanbul sharply decreases — and consequentially cruising is triggered — beyond an occupancy rate of 85 per cent.

In the current paper we estimate the marginal effect of high parking occupancy rates on the walking distance between parking spot and residential destination for several neighbourhoods in Amsterdam. While the effect of parking occupancy on walking has been given ample attention in theoretical studies (Arnott *et al*., 1991; Arnott and Rowse, 1999; Martens *et al*., 2010; Arnott, 2014; Zakharenko, 2016), to our knowledge this is the first study that investigates this relationship empirically. We pay explicit attention to the *Shoup rule-of-thumb* and investigate whether it holds in a residential context. The focus on the level of the occupancy rate that triggers cruising for parking is also relevant from a policy perspective. The current parking policy in the studied areas — neighbourhoods in the west and east of Amsterdam — uses a target maximum occupancy rate of 90 per cent (Gemeente Amsterdam, 2012).

More specifically, we estimate the effect of the *hourly* occupancy rate in a street on the walking distance of residents who live in this street and park near their residence, which allows us to derive the external effect of a driver's decision to (continue to) park in a certain street on other (potential) parkers. Our estimation procedure uses (confidential) licence plate data, collected by scanner cars that made hourly rounds in specific neighbourhoods. We identify the marginal effect of occupancy on walking using both spatial and spatio-temporal variations in the data. Given assumptions on the relationship between search costs and walking distance, and using earlier estimates of the willingness-to-pay for parking permits (Van Ommeren *et al*., 2011), our results allow us to identify whether the current target occupancy rate differs from the optimal occupancy rate.

Our main finding is that walking distances start to increase beyond occupancy rates above 85 per cent, in line with Shoup (2006). The extent of additional walking is limited: each parked car imposes only 8 m walking distance on every next resident that wants to park. Hence, residential parking seems to differ from parking in other contexts, where

[2]See Inci (2015) for a review of parking economics literature.

the additional costs — mainly cruising — are estimated to be much higher (Millard-Ball *et al*., 2014; Inci *et al*., 2017). Arguably, as explained above, this occurs because residents differ spatially in their demand for parking. The main policy implication of this paper is that it might be welfare enhancing to provide parking permits until almost all parking spaces are occupied in the evening, when the inflow rate into parking is low. This conclusion is in line with results from modelling exercises that show that optimal occupancy rates may be higher than 85 per cent in the case of low parking turnover at the end of the day (Martens *et al*., 2010; Zakharenko, 2016).

The rest of this paper is organised as follows. In Section 2 we describe the parking policy in Amsterdam, and the data. In Section 3 we provide the empirical results and Section 4 discusses the implications of our results for parking permit provision schemes. Section 5 concludes.

2.0 Institutional Environment and Data

In all areas of Amsterdam within the A10 ring road, on the city-side of the IJ river, parking permit schemes are in place, with a restriction of maximally one permit per household.[3] Permits are issued to residents who own a car. Prices of these permits vary from €96 to €553 annually (Gemeente Amsterdam, 2015). The number of permits is restricted, based on parking capacity. Therefore, in some neighbourhoods there is excess demand for permits, resulting in waiting lists (De Groote *et al*., 2016). Our primary data were collected in December 2015, in neighbourhoods just outside of the historic centre (see Figure 1). These neighbourhoods are primarily residential areas, and prices of parking permits range from €265 to €330 annually. We shall distinguish between east and west neighbourhoods. In a few west neighbourhoods, waiting lists apply. Residents on this list receive a 'spillover-permit', which allows them to park in a nearby permit area with excess supply. The streets in these neighbourhoods always allow for non-residential (visitor) parking. On-street prices for non-residents range from €2.40 to €4 per hour.

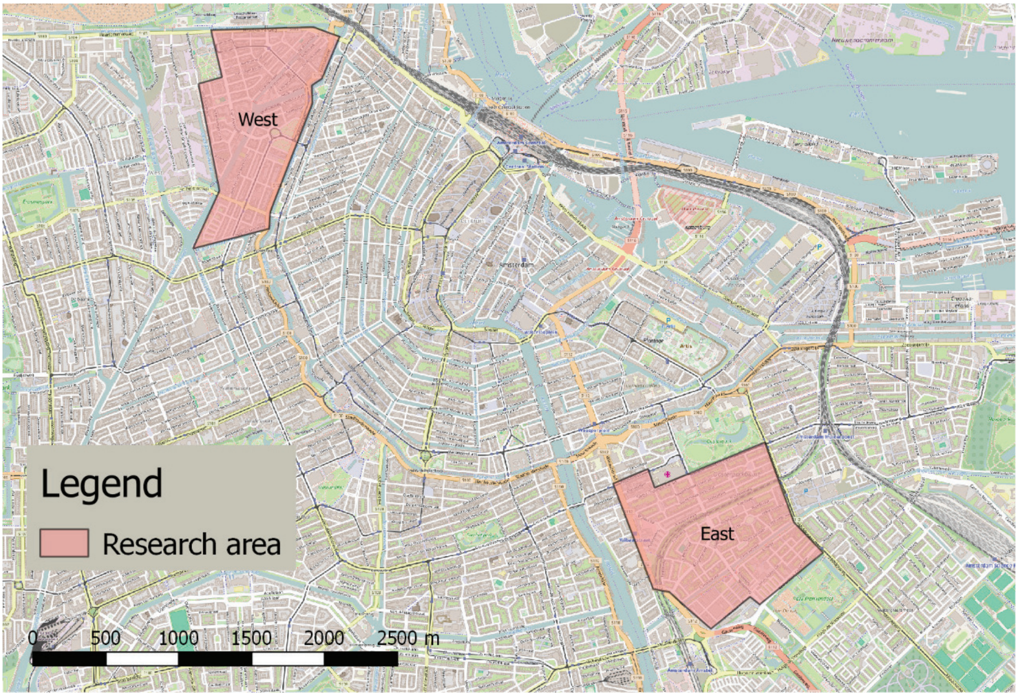
In December 2015, during 18 hourly scan rounds (between 6 a.m. and 11 p.m.), the licence plate numbers of all parked cars in a street were registered.[4] In the east area this was done during three consecutive days, in the west during one day. Licence plate numbers were matched with the Amsterdam parking permit holder database. For each permit holder who parked, we know the residential location on a six-digit postcode level.[5] We observe the hour in which permit holders parked their car (between two rounds). We thus have information on when residents parked, where they parked, and where they live. Part (a) in Figure 2 shows the distribution of inflow of residents during the day. A clear peak is visible starting from about 3 p.m., when residents start to return home from work.

[3] Similar residential permit schemes are in place in other cities in the world, such as Toronto, San Francisco, Paris, and Moscow.

[4] We geocoded streets using the *Nationaal Wegenbestand* data provided by the Dutch Highway Authority (*Rijkswaterstaat*). The definition of streets here refers to street sections between two junctions. The average length of a street section in our sample is 80 m.

[5] In the Netherlands, six-digit postcodes cover about half a street, comparable to a US census block. In Amsterdam, six-digit postcodes contain 12 houses on average.

Figure 1
Research Areas in Amsterdam



Using information on all parked cars, and the number of parking spaces per street,[6] we calculate the occupancy rate per street. Given the assumption that drivers start to search if they do not find a parking space in front of their home, the relevant occupancy rate is the occupancy rate near the residence, and not the one in the street where the parking space is eventually found. Therefore, for each resident in our data we match the postcode centroid of their residence to the nearest street section. In our analysis we use the one-hour lag of the occupancy rate in the residential street as the independent variable of interest. Part (b) in Figure 2 shows the distribution of the occupancy rate. There are few observations where the occupancy rate is lower than 50 per cent.

Residents with cars receive a parking permit that is valid for a specific area close to their residence. We only use those observations for which the parking location and the residential location are both within the research area. We define walking distance as the *road network* distance between the centroid of the street section in which the car is parked and the centroid of the six-digit postcode area. This means we assume that people walk along the road network from their parking location to their home. Because we only observe parking locations at the street section centroid level, walking distance is measured with an error that tends to be positive: even if all residents would park exactly in front of their homes, we still measure a positive average walking distance.

[6]Provided by the municipality of Amsterdam on request.

Figure 2
Distribution of Main Variables

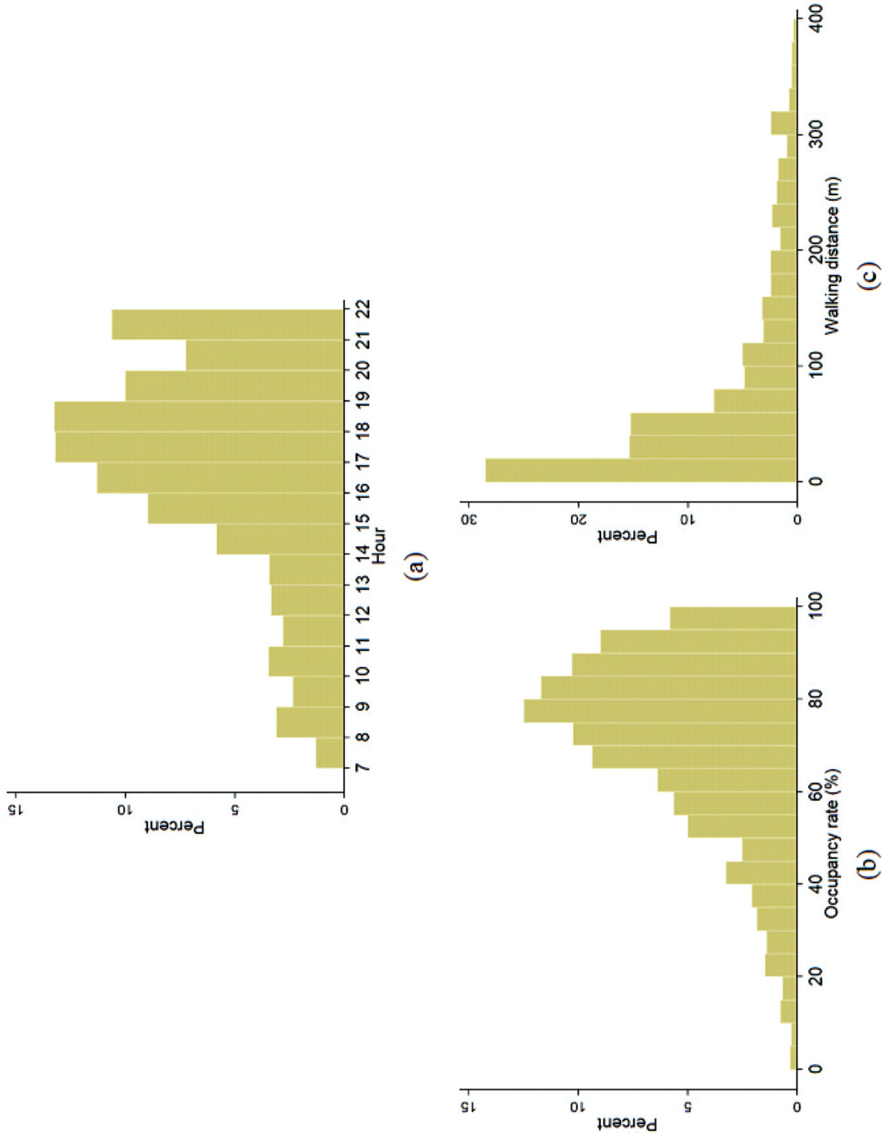


Figure 3
Distributions of Secondary Variables

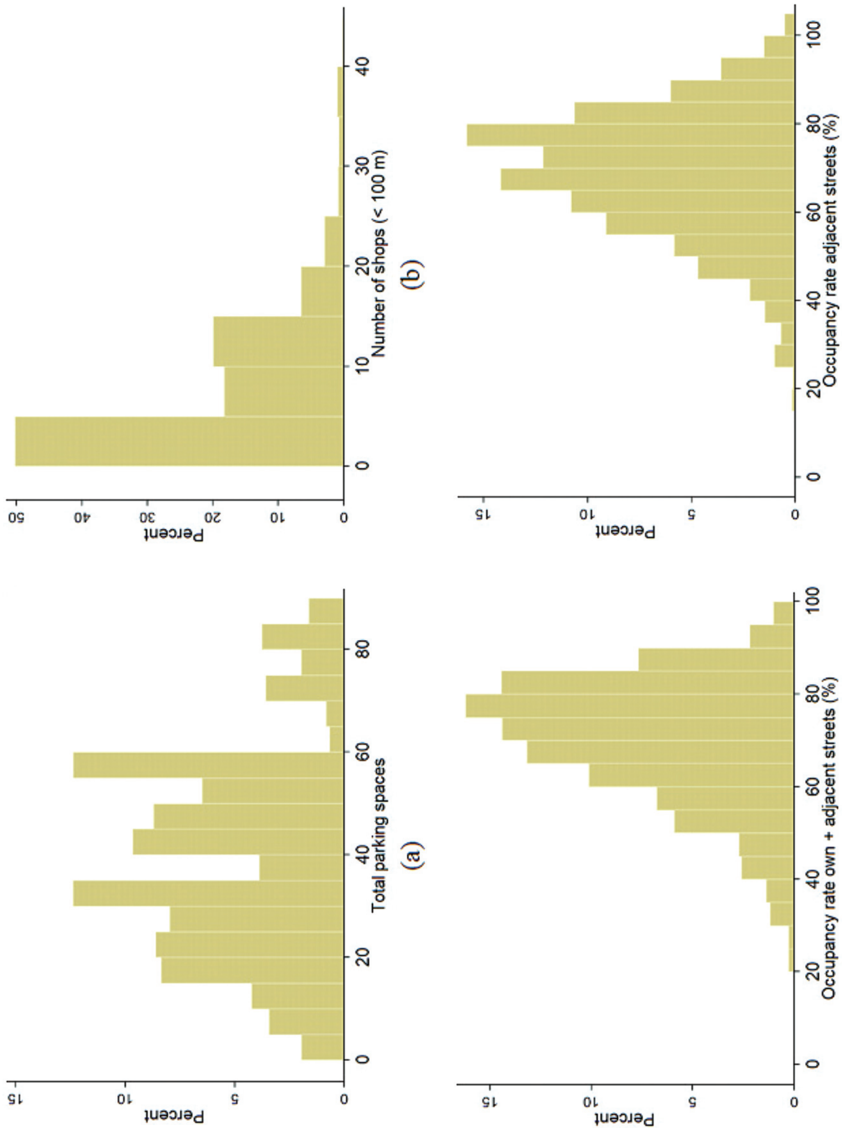


Table 1
Summary Statistics

Variables	*(1)* *N*	*(2)* *Mean*	*(3)* *Std. dev.*	*(4)* *Min*	*(5)* *Max*
Walking distance (m)	3,515	81.52	88.08	0.228	395.6
Occupancy rate (%)	3,515	70.49	19.63	3.448	100
Hour	3,515	16.24	3.607	7	22
Total parking spaces	3,515	39.57	20.18	1	86
Number of shops (<100 m)	3,515	6.822	7.230	0	41
Occupancy rate own + adjacent streets (%)	2,396	70.17	13.52	21.75	100
Occupancy rate adjacent streets (%)	2,396	68.87	14.32	18.51	100

For the majority of drivers, it seems reasonable to assume that the residential location is the travel destination. In a few cases the destination might differ (family visit, shopping, and so on). However, because this measurement error is random and present in the *dependent* variable, the effect of the occupancy rate on walking distance will still be consistently estimated (Wooldridge, 2002). To avoid the effect of extreme outliers, including those who use the car for shopping or visiting friends, we exclude distances of more than 400 m (3.6 per cent of observations). Part (c) in Figure 2 shows the distribution of walking distance. Few walking distances exceed 200 m.

In some of our analyses, we control for the number of parking spaces in the residential street to account for spatial differences in local parking supply (see part (a) in Figure 3). In the sensitivity analysis we control for the number of shops within 100 m from the residence (part (b), Figure 3), and we use an alternative measure of the occupancy rate, which refers to the occupancy rates in adjacent streets, both including (part (c), Figure 3) and excluding the own street (part (d), Figure 3).

In Table 1 descriptive statistics are shown.[7] We have 3,515 observations. For a subset of 2,396 observations, we have information on the occupancy rate in adjacent streets. On average, walking distance is 81.5 m, the occupancy rate is 70 per cent, and streets have 40 parking spaces. We use the descriptive statistics to get an idea of the *extent* of walking costs relative to total search costs, in monetary terms. Given a value of travel time of €9.25 per hour (Kouwenhoven *et al*., 2014), a walking speed of 4 km per hour, and average daily private search costs of €1.15 (Van Ommeren *et al*., 2011), the share of walking costs in total search costs is only 19.76 per cent.[8] Note that this result should be interpreted with caution, but strongly suggests that walking costs are relatively small compared to in-car cruising costs.

[7]Data on the number of shops stems from the 2013 *Functiekaart* (non-residential function map), provided by the municipality of Amsterdam (http://maps.amsterdam.nl/functiekaart).

[8]The annual walking costs in our data are €83 (the time costs of the average daily 81.2 m walks to and from the car, based on 44 work weeks of five days). The annual private search costs in Amsterdam are €420 on average, or equivalently €1.15 per day, according to Van Ommeren *et al*. (2011).

3.0 Empirical Results

3.1 Empirical strategy

In our empirical strategy we start with a specification in which we identify the causal effect of occupancy rates on walking distance using s*patial* variation (between street sections in the same neighbourhood) in occupancy rates:

$$W_{irndt} = \alpha + \beta O_{rndt} + \gamma S_{rn} + \delta S_{rn}^2 + \eta_n + \theta_t + \iota_d + \epsilon_{irndt}. \quad (1)$$

Here W_{irndt} denotes the walking distance for parker i in street r in neighbourhood n at day of the week d at time t. O_{rndt} is the occupancy rate and S_{rn} the number of parking spaces. η_n are neighbourhood fixed effects, θ_t are hour fixed effects, ι_d are day fixed effects, and ϵ_{irnt} is the error term. We estimate the occupancy rate that triggers walking by using a flexible dummy specification of O and examine at what point the occupancy rate increases walking distance. We estimate the marginal effect of the occupancy rate for values below and above 85 per cent using a piecewise linear function.

We also estimate models using *spatiotemporal* variation, using time variation in occupancy rates within street sections, and therefore controlling for unobserved characteristics related to street sections and the hour of day:

$$W_{irdt} = \alpha + \beta O_{rdt} + \eta_r + \theta_t + \iota_d + \epsilon_{irdt}, \quad (2)$$

where η_r are street section fixed effects. In all regressions we cluster standard errors at the (residential) street section-hour level because the occupancy rate is measured at this level, and the errors of observations in the same hour at the same street section may thus be correlated (Moulton, 1986).

3.2 Main results

In Table 2 the main results are presented. Columns (1), (2), and (3) refer to equation (1) and the other columns refer to equation (2). According to the results presented in column (1), a 10 per cent increase in the occupancy rate leads to 3.7 m additional walking distance on average. The flexible specification in column (2) suggests that the effect of occupancy rates is non-linear (see part (a) in Figure 4). From 85 per cent onwards, the marginal effect is positive and statistically significant. Residents arriving in streets with occupancy rates between 85 and 90 per cent walk 15.7 m further, on average, than those arriving in streets with an occupancy rate below 50 per cent. If we assume a break in the marginal effect of occupancy rates at 85 per cent, following Shoup (2006), we find that the occupancy rate has no effect below 85 per cent, and each percentage point increase in the occupancy rate beyond 85 per cent leads to an increase in walking distance of 3.3 m for *each* subsequent parker. In a representative street with 40 parking spaces (the average number), each parking car beyond 85 per cent increases the occupancy rate by 2.5 percentage points, and thus raises the walking distance of later arrivals by 8.2 m. The coefficients for total parking spaces and its square are not statistically significant.

Making use of spatiotemporal variation in identifying the effect of occupancy rates, in columns (4), (5), and (6), leads to comparable results. In column (4) the effect of occupancy rates takes off around 85 per cent, but the effect is only statistically significant beyond 90 per cent occupancy (see part (b) in Figure 4). Furthermore, the marginal effect of occupancy rates beyond 85 per cent in column (6) is significant, and remarkably similar to the

Table 2
Main Regression Results. Dependent Variable: Walking Distance (m)

	Spatial identifying variation			*Spatiotemporal identifying variation*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Occupancy rate (%)	0.366***			0.431***		
	(0.115)			(0.137)		
Occupancy rate 50–60%		−5.480			−5.893	
		(5.559)			(5.852)	
Occupancy rate 60–70%		−3.420			−6.403	
		(6.335)			(6.216)	
Occupancy rate 70–80%		−0.163			−5.378	
		(5.521)			(6.630)	
Occupancy rate 80–85%		−2.856			0.763	
		(6.848)			(7.385)	
Occupancy rate 85–90%		15.74**			13.12	
		(7.115)			(8.356)	
Occupancy rate 90–95%		31.35***			30.08***	
		(11.35)			(9.377)	
Occupancy rate 95–100%		30.84***			32.48***	
		(11.20)			(10.73)	
Occupancy rate (if O = <85)			0.00778			0.0669
			(0.102)			(0.143)
Occupancy rate (if O > 85)			3.282***			3.193***
			(0.874)			(0.663)
Total parking spaces	0.0518	0.206	0.388			
	(0.366)	(0.366)	(0.389)			
Total parking spaces^2	−0.00276	−0.00412	−0.00556			
	(0.00408)	(0.00399)	(0.00417)			
Day and hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Neighbourhood FE	Yes	Yes	Yes	No	No	No
Street section FE	No	No	No	Yes	Yes	Yes
Observations	3,515	3,515	3,515	3,515	3,515	3,515
R-squared	0.105	0.116	0.116	0.284	0.292	0.291

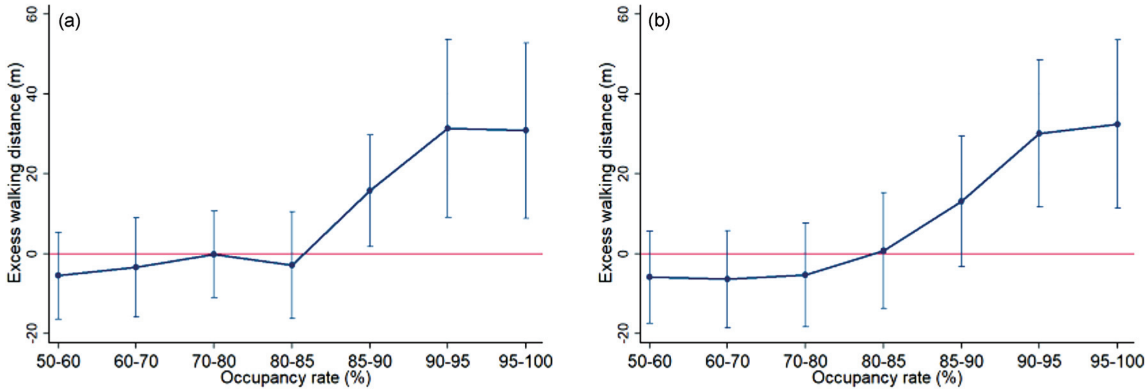
Notes: Cluster-robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

estimate in column (3) (3.193 vs. 3.282). Each parking car in a representative street (40 parking spaces) leads to an 8 m increase for the marginal parking resident, according to this model. We consider the latter result our preferred estimate.

The results from columns (2) and (4) indicate that the *Shoup rule-of-thumb* (85 per cent) is a good approximation of the occupancy rate that triggers searching for a parking space. A kink in the effect of occupancy rates is discernible between 80 and 85 per cent in both parts of Figure 4. This result is similar to the results of Millard-Ball *et al.* (2014) and Inci *et al.* (2017). The functional form of the relationship seems linear between 80 and 95 per cent occupancy, after which it stabilises. This finding corroborates the results from a simulation exercise by Levy *et al.* (2013), where it was shown that walking distance increases linearly with occupancy beyond 85 per cent.

The levelling off of the effect above 95 per cent occupancy may have several reasons. First, occupancy rates above 95 per cent are rare in our data (see Figure 2). In other

Figure 4
Marginal Effects Plot



Part (a) refers to column (2) in Table 2, and part (b) refers to column (5) in Table 2. The dots represent the point estimates of the interval dummies (x axis). The vertical lines represent the 95 per cent confidence intervals.

words, we have few observations of arriving residents when the occupancy rate is very high. This means that the exact effect of very high occupancies is difficult to estimate. In our data, we cannot reject the hypothesis that the effect of occupancy rate above 95 per cent exceeds the effect of the occupancy rate between 90 and 95 per cent. It is plausible that with larger data sets, and therefore smaller standard errors, we would find that the effect of occupancy still increases above 95 per cent. Second, we have measurement error in the occupancy rate (we measure it hourly), which means that the effect of occupancy rate will be biased downwards. This may be more problematic for high values of the occupancy rate. Finally, note that if the occupancy rate is really 100 per cent during a full hour (within the street and the adjacent neighbourhood), it is likely that arriving residents park outside the area included in our analysis and are therefore not observed.

As pointed out in a recent paper by Arnott and Williams (2017), many theoretical models of parking use the so-called *binomial approximation*, according to which *in-car cruising time*, and therefore cruising distance, is proportional to $1/(1 - occupancy)$. To test this theory, one would ideally regress the logarithm of cruising distance on the logarithm of $1/(1 - occupancy)$. If the prediction holds, then the estimated coefficient would be equal to 1. While we do not observe cruising distance directly, our data allow us to test whether the prediction holds for walking distance. Using a specification based on equation (2), we find that this coefficient is much lower than 1, and equal to 0.23. So this prediction does not hold. The implication is that either the *binomial approximation* is a bad one in the context of residential parking or, alternatively, that when cruising for a vacant parking space, motorists circle around their destination, so walking distance increases less than proportional with cruising time. We think the latter is the most plausible explanation. In our welfare analysis in Section 4, we shall therefore allow for the possibility that cruising costs increase disproportionately with walking distance.

3.3 Sensitivity analysis

In Table 3 we check whether our results are robust to including additional controls and employing different definitions of occupancy rate. We use a flexible dummy specification of the occupancy rate because this approach does not assume a (partially) linear effect of occupancy rates. We check the robustness for both identification methods (spatial and temporal variation).

In columns (1) and (2) we include the number of shops within a 100 m radius from the centroid of the residential street. The aim is to control for different parking dynamics in shopping neighbourhoods. The more shops there are in the neighbourhood, the more volatile the occupancy rate may be, which may lead to measurement error of the occupancy rate. Controlling for shopping districts barely increases the R-squared of the models, and the estimates in columns (1) and (2) are similar to those obtained in Table 2, columns (2) and (5).

In columns (3) and (4) we use a definition of occupancy rate that refers to the occupancy rate in the streets surrounding the residence, calculated using at least one adjacent street section on each side of the residential street section. The estimates again show that in general, above 80 per cent occupancy walking distances are much higher than below 80 per cent, except in the upper range of 95–100 per cent. From part (c) in Figure 3 it can be gathered that very few areas have such a high occupancy rate. Overall, it seems that occupancy rates measured at the surrounding area level trigger walking earlier (starting

Table 3
Robustness Checks. Dependent Variable: Walking Distance (m)

	(1)	(2)	(3)	(4)	(5)	(6)
Own street						
Occupancy rate 50–60%	−5.455	−6.394			−11.67	−7.757
	(5.535)	(5.887)			(7.228)	(8.024)
Occupancy rate 60–70%	−2.982	−6.650			−9.139	−10.75
	(6.322)	(6.243)			(7.314)	(7.623)
Occupancy rate 70–80%	0.120	−5.416			−9.118	−13.83
	(5.516)	(6.651)			(6.820)	(8.726)
Occupancy rate 80–85%	−2.712	0.712			−6.715	−8.668
	(6.869)	(7.405)			(8.572)	(9.947)
Occupancy rate 85–90%	15.60**	13.27			7.694	1.573
	(7.140)	(8.362)			(8.614)	(10.91)
Occupancy rate 90–95%	31.06***	30.17***			35.09***	21.58*
	(11.60)	(9.431)			(13.09)	(11.98)
Occupancy rate 95–100%	29.74**	32.62***			35.30***	23.17
	(11.57)	(10.82)			(12.22)	(14.09)
Own street + adjacent streets						
Occupancy rate 50–60%			4.236	13.37*		
			(7.604)	(7.729)		
Occupancy rate 60–70%			7.558	14.44		
			(7.726)	(8.773)		
Occupancy rate 70–80%			10.62	9.138		
			(7.566)	(9.188)		
Occupancy rate 80–85%			35.52***	31.94***		
			(9.636)	(11.29)		
Occupancy rate 85–90%			44.39***	47.49***		
			(11.41)	(12.78)		
Occupancy rate 90–95%			49.17***	54.95***		
			(13.84)	(16.59)		
Occupancy rate 95–100%			14.72	13.63		
			(18.60)	(19.41)		
Adjacent streets						
Occupancy rate 50–60%					3.140	3.418
					(6.544)	(7.124)
Occupancy rate 60–70%					15.11**	7.757
					(7.187)	(7.890)
Occupancy rate 70–80%					25.51***	13.73
					(8.338)	(8.971)
Occupancy rate 80–85%					11.45	2.744
					(9.945)	(10.43)
Occupancy rate 85–90%					24.79**	25.35**
					(10.09)	(12.27)
Occupancy rate 90–95%					11.37	1.674
					(11.22)	(12.57)
Occupancy rate 95–100%					−13.71	12.25
					(12.65)	(16.75)

Table 3
Continued

	(1)	(2)	(3)	(4)	(5)	(6)
Number of shops (<100 m)	0.323	0.799				
	(0.375)	(0.488)				
Total parking spaces	0.123		0.118		0.432	
	(0.397)		(0.465)		(0.474)	
Total parking spaces^2	−0.00315		−0.00212		−0.00554	
	(0.00435)		(0.00691)		(0.00692)	
Day and hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Neighbourhood FE	Yes	No	Yes	No	Yes	No
Street section FE	No	Yes	No	Yes	No	Yes
Observations	3,515	3,515	2,396	2,396	2,396	2,396
R-squared	0.117	0.293	0.166	0.330	0.185	0.332

Notes: Cluster-robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

from between 50 per cent and 80 per cent), and more gravely (49–55 m at occupancy rates between 90 and 95 per cent). This seems to make sense because measuring occupancy rate at a broader level decreases the chance that the measured occupancy rates are incidental or extremely local.

In columns (5) and (6) we estimate the effect of (own-street) occupancy rate, conditional on the occupancy rate in adjacent streets. The estimates that are identified using spatial variation, in column (5), are comparable to the results from Table 2, columns (2) and (5), although walking distances are only significantly affected beyond 90 per cent occupancy. The model in column (6), based on spatiotemporal variation, fails to deliver significant results for the own-street occupancy rate. The results still suggest that the *Shoup rule-of-thumb* may hold, as both models show a kink in the effect of occupancy rates around 85 per cent. Overall, our main results are robust to including additional controls and using a different definition of occupancy rates.

4.0 Welfare Discussion

The results from the previous section imply that in a representative street with 40 parking spaces, each driver who parks beyond an occupancy rate of 85 per cent imposes 8 m walking distance on every next driver, equal to about two car lengths. This result confirms that also in residential contexts, searching for parking, indicated by excess walking, rises with occupancy beyond 85 per cent. In this section we use this result to estimate the *extent* of searching beyond 85 per cent and we calculate the optimal occupancy target. We ignore the effects on non-residential parkers (for example, visitors) because: (1) late in the evening, when occupancy rates are high, demand for parking by visitors is very low; and (2) parking fees are set (between €2.40 and €4 per hour) so that parking occupancy during the day, when visitors tend to park, is rarely high.

Zakharenko (2016) notes that parking externalities differ in one important respect from traditional road-congestion externalities: the walking externality imposed by a resident who parks for a certain duration depends on the number of subsequent arrivals. To make this intuitive, consider a resident who parks in a residential street for one hour. If there is no other resident who aims to park in the same street during this hour, then this car imposes no externality. If one car arrives during that hour, the imposed walking externality is 8 m according to our estimates. If two cars arrive, the externality is 16 m, because both later arrivals have to walk 8 m further. The walking externality of a resident arriving home in the evening can thus be calculated by multiplying the number of subsequent arrivals (until the resident leaves in the morning) by 8 m.

It is also interesting to calculate the implied external walking cost per subsequent arrival. Given an assumption of walking speed (4 km/h) and a value of time (€9.25 per hour), the monetary equivalent of walking 8 m to and from the parked car is 3.7 cents. To calculate the total external cost, we wish to include in-vehicle search time. Given the assumption that walking costs are 19.76 per cent of total search costs, the associated walking and search costs are equal to 18.7 cents for each subsequent arrival.

To derive the marginal external cost of parking, one needs to know the exact order of arrival and departure of all residents. We avoid this cumbersome calculation by assuming that the occupancy rate increases monotonically in the evening (so residents do not depart). It then immediately follows that the maximum marginal external cost is imposed by the resident who parks when the occupancy rate is exactly equal to the critical level of 85 per cent (when the occupancy rate is below 85 per cent, there are no external costs; when the occupancy rate exceeds 85 per cent, excess walking occurs). This maximum marginal external cost is also a relevant decision variable in setting the occupancy target of residential parking areas because policy makers have no information on the exact order of arrival. Most likely, a policy maker's best guess is that the marginal permit holder will arrive at the average arrival time, when the occupancy rate is generally below critical levels.

For the representative street of 40 parking spaces, there are maximally six arrivals beyond the critical occupancy rate (15 per cent of 40 parking spaces), so the maximum marginal external costs amount to 6×18.7 cents per day, or €1.12 per day. Note that this may be an overestimate because the mean number of parking permits as a percentage of the number of parking spaces is 89 per cent, close to the target occupancy rate of 90 per cent (Gemeente Amsterdam, 2012), far less than the 100 per cent assumed above. On the other hand, it may be an underestimate because we ignore any parking turnover during the night. The annual marginal external cost of residential parking is therefore (maximally) €247 per year, assuming five working days and 44 annual working weeks.[9]

Let us now calculate the marginal benefit of residential parking. According to an estimate based on house prices in Amsterdam by Van Ommeren *et al.* (2011), the marginal willingness-to-pay for parking when the resident has to cruise — so net of cruising costs — is about €9 per day or €3,250 annually.[10] This is one order of magnitude higher than the marginal costs. It follows that the optimal occupancy level is close to 100 per cent in the

[9]This is remarkably close to the annual price of a parking permit (between €265 and €330 annually).

[10]This is consistent with off-street garage subscriptions that cost €273.18 in the eastern part of Amsterdam, and €384.68 in the west, at the time of data collection (www.q-park.nl/nl/parkeren-bij-q-park/per-stad). Note that the marginal willingness-to-pay is net of private cruising costs, so the marginal external costs equal the marginal social costs.

Table 4
Maximum Marginal External Costs at 100% Occupancy Under Different Scenarios

	Relation between excess walking and searching		
Daily search costs	*(1) Square root*	*(2) Proportional*	*(3) Quadratic*
Low: €0.50	€40	€107	€232
Medium: €1.15	€93	€247	€513
High: €5	€403	€1,075	€2,230

evening. This implies the government should issue permits such that the occupancy rate is close to 100 per cent.

These welfare calculations are based on a number of assumptions. First, our empirical analysis rests on the assumptions that people walk along the road network to their home, and that the residence is the travel destination. We believe that these assumptions are not problematic. Second, to add insight to our results, we made assumptions about the value of travel time and walking speed. The results of our welfare analysis do *not* depend on these assumptions. In contrast, the welfare calculations do depend on the assumptions concerning: (1) the relationship between walking and searching; and (2) the *average* daily private search costs. We assess the sensitivity of the welfare analysis to these assumptions in Table 4. In the columns we alternate the type of relationship between walking and searching from marginally diminishing to quadratic. In the rows we alternate the assumption on daily private cruising costs. The middle value refers to the base scenario. It is shown that even in the extreme scenario where searching grows quadratically with walking distance, and average daily search costs are €5, the marginal external costs of parking at full occupancy do not exceed the marginal willingness-to-pay for parking (with cruising) of €3,250. Therefore, the implication of our welfare analysis, that the optimal occupancy rate is close to 100 per cent, is robust to these assumptions.

5.0 Conclusion

In this paper we use hourly parking data obtained by scanner cars to investigate the effect of parking occupancy rates on walking distance, in a residential context, in Amsterdam. The results indicate that excess walking arises at occupancy rates above 85 per cent. However, the extent of walking is limited: beyond an occupancy rate of 85 per cent, every parker imposes 8 m on each subsequent parker; and the associated marginal external costs of parking are an order of magnitude lower than the marginal benefits of parking. Although we find evidence for the *Shoup rule-of-thumb*, it appears that allowing for increased walking, and therefore cruising, is welfare enhancing, compared to policies that limit the occupancy rate to 85 per cent (or even 90 per cent, such as in Amsterdam). This result seems to contrast with studies that investigate the extent of searching above 85 per cent in other contexts (CBD, shopping centres, and tourist areas) that estimate much higher external costs, essentially because the parking inflow rate is much higher (Millard-Ball *et al.*, 2014; Inci *et al.*, 2017).

Our study suggests that policy makers must consider the vast differences between residential parking and other types of parking: solutions that alleviate parking problems in CBD or shopping contexts may have adverse welfare effects in residential contexts. In essence, residents differ spatially in their demand for parking because they differ in the location where they want to park, and the inflow rate into parking is low in the evening. This study suggests that policies that regulate residential parking should set target occupancy rates close to 100 per cent, so that almost all parking spaces are occupied at the end of the evening. To formulate it differently, policy makers should be aware that the additional walking times, and (most likely) search costs, are low compared to the marginal willingness-to-pay for residential parking.

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